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Review Article

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Adaptive Repayment Optimisation for SME Lending: A Stochastic Programming Framework with Generative AI Explanation

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ABSTRACT
This paper introduces the Adaptive Repayment Optimisation Engine (AROE), a novel framework that applies constrained stochastic optimisation to the design of loan repayment schedules for small and medium-sized enterprises (SMEs). Unlike fixed-payment or simple revenue-share structures currently dominant in UK SME lending, AROE decomposes each borrower's cash flow into trend, seasonality, cyclicality, and idiosyncratic volatility components, then uses Monte Carlo simulation and bounded quasi-Newton optimisation to find repayment schedules that minimise the probability of payment distress subject to lender return constraints. A generative AI explanation layer then translates the mathematical output into natural language rationale serving three audiences: borrower, underwriter, and regulator. We validate the framework on a synthetic universe of 10,000 UK SMEs calibrated to ONS, British Business Bank, and sectoral insolvency data across ten SIC-aligned industry sectors and twelve UK regions. Computational experiments demonstrate that AROE-optimised schedules reduce payment distress probability by a mean of 7.7–26.6% compared to equivalent fixed-payment benchmarks, with the largest improvements observed in sectors exhibiting high revenue volatility and pronounced seasonality (Construction, Accommodation s Food, Retail). We discuss the implications for FCA Consumer Duty compliance, IFRS 6 provisioning, and the commercial viability of the approach as a SaaS product for lending platforms. The framework contributes to the operations research literature by bridging stochastic programming, explainable AI, and financial regulation in a novel application domain.

Keywords: Stochastic Programming, SME Lending, Repayment Optimisation, Operations Research, Explainable AI, Consumer Duty, Cash Flow Modelling, Monte Carlo Simulation

Introduction

Access to appropriately structured finance remains one of the most significant constraints on UK small and medium-sized enterprise (SME) growth. The British Business Bank's Small Business Finance Markets report has consistently documented the tension between lending supply and SME demand, with gross bank lending to SMEs declining by 6% in recent years even as alternative lenders have expanded their market share [1]. While considerable innovation has occurred in credit assessment—through the application of machine learning to underwriting, alternative data integration via Open Banking, and automated document processing—comparatively little attention has been paid to the structure of the repayment obligation itself.

The dominant paradigm in UK SME lending remains the fixed monthly repayment. A borrower who takes a £50,000 term loan over 36 months pays an identical amount each month regardless of whether the business is experiencing peak seasonal demand or a cyclical trough. A small but growing number of alternative lenders—notably Liberis, 365 Finance, and Capify—have introduced revenue-share models where repayments are calculated as a fixed percentage of daily card turnover. While this represents a step toward cash flow alignment, such models are heuristic in nature: they do not formally optimise the repayment structure against multiple competing objectives, nor do they account for the full distributional properties of the borrower's cash flow process.

This paper argues that the design of SME loan repayment schedules is fundamentally an operations research problem amenable to stochastic programming techniques. Specifically, we frame it as a constrained optimisation under uncertainty: given a stochastic model of the borrower's future cash flows, find the repayment schedule that minimises the probability of payment distress—defined as a payment exceeding a specified fraction of available cash—subject to the lender achieving a

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target internal rate of return, the total repayment equalling the contractual obligation, and smoothness constraints that ensure the schedule is practically implementable.

We introduce the **Adaptive Repayment Optimisation Engine (AROE),** a framework comprising four integrated components: (i) a time-series cash flow decomposer that separates trend, seasonality, cyclicality, and idiosyncratic volatility from Open Banking transaction data; (ii) a Monte Carlo forward simulation engine; (iii) a bounded quasi-Newton optimiser operating on a parameterised schedule space; and (iv) a generative AI explanation layer that produces natural language rationale for the optimised schedule.

The contribution of this paper is fourfold. First, we formalise the SME repayment scheduling problem as a stochastic program and demonstrate its tractability using standard gradient-based solvers. Second, we validate the framework on a large-scale synthetic dataset of 10,000 UK SMEs calibrated to empirical sectoral and regional characteristics. Third, we demonstrate how generative AI can serve as the "last mile" of an OR pipeline, translating mathematical optimisation output into regulatory-quality natural language explanation—a novel integration with implications for the growing field of explainable operations research. Fourth, we situate the framework within the UK's evolving regulatory landscape, particularly the FCA's Consumer Duty (PS22/6) and the Basel Committee's emerging guidance on AI model risk management, arguing that adaptive repayment scheduling represents a concrete, auditable mechanism for demonstrating good customer outcomes.

The remainder of the paper is organised as follows. Section 2 reviews the relevant literature across four streams: operations research in financial services, SME lending and cash flow modelling, adaptive repayment mechanisms, and explainable AI in credit decisions. Section 3 presents the mathematical formulation and the AROE architecture. Section 4 describes the synthetic data generation methodology. Section 5 reports the computational experiments and results. Section 6 discusses the implications, limitations, and directions for future research. Section 7 concludes.

Literature Review

Operations Research in Financial Services

The application of operations research to financial decision-making has a rich history, with stochastic programming occupying a central position since the foundational work of [2,3]. Birge and provide the canonical textbook treatment, demonstrating how multi-stage stochastic programs can model sequential decision-making under uncertainty across finance, logistics, and resource allocation domains [4]. In mortgage finance specifically, Rasmussen and Clausen formulated the Danish mortgagor's problem as a multi-stage stochastic integer program, demonstrating that optimal mortgage portfolios should be more diversified and more frequently rebalanced than prevailing practice [5].

Closer to the present work, Chun and Lejeune developed risk-based loan pricing models using mixed-integer nonlinear stochastic programming with Value-at-Risk and Conditional Value-at-Risk constraints, demonstrating how OR techniques can integrate credit risk, willingness-to-pay, and portfolio marginal risk contribution in a unified pricing framework [6]. Their work established the computational tractability of loan-level optimisation but focused on pricing rather than repayment structure. The sample average approximation method provides the theoretical justification for the Monte Carlo approach we employ, demonstrating that solutions obtained from sample-based approximations converge to the true optimal as the sample size increases [7].

Powell provides a unifying framework for stochastic optimisation, identifying four fundamental classes of policies: myopic, lookahead, policy function approximation, and value function approximation [8]. The AROE framework falls within the policy function approximation class, where we parameterise the repayment schedule through seasonal multipliers and optimise the parameters against a sampled approximation of the objective.

SME Lending, Cash Flow Analysis, and Open Banking

The UK SME lending landscape has undergone significant structural change over the past decade. Traditional banks have progressively exited segments of the SME lending market, creating space for alternative lenders, peer-to-peer platforms, and fintech entrants [1]. The Competition and Markets Authority's Open Banking initiative, fully operational since 2018, has enabled programmatic access to SME transaction data via standardised APIs, fundamentally changing the data available for credit assessment.

Cash flow analysis for SMEs has traditionally relied on management accounts, bank statements, and VAT returns. Berg, Burg, Gombović, and Puri demonstrated that digital footprint data—including web traffic, app usage, and online transaction patterns—can significantly improve SME credit prediction compared to traditional credit bureau scores [9]. The time-series properties of SME cash flows are well-documented in the accounting literature. Lorek and Willinger established that cash flow time series exhibit significant autocorrelation, seasonality, and heteroscedasticity—properties that are poorly captured by aggregate annual metrics but are directly observable in monthly Open Banking data [10].

Adaptive and Revenue-Linked Repayment Mechanisms

Revenue-based financing (RBF) has emerged as an alternative to fixed-payment lending for businesses with variable cash flows. In the UK, firms such as Liberis and Capify offer merchant cash advances where repayments are a fixed percentage of daily card turnover, effectively creating an automatic cash flow alignment mechanism. However, as Robb and Robinson note in their analysis of small business capital structure, the simplicity of such mechanisms comes at the cost of suboptimality: a fixed percentage does not account for the shape of the cash flow distribution, the presence of existing debt service, or the lender's required return [11].

The academic literature on optimal repayment scheduling is surprisingly sparse. Gupta et al. developed an integer programming model for loan payment scheduling [12]. More recently, dynamic repayment models have appeared in the fintech industry but have not been formally analysed in the OR literature. To our knowledge, no prior work has formulated the

SME repayment scheduling problem as a constrained stochastic program with explicit distress-minimisation objectives, which represents the principal methodological contribution of this paper.

Explainable AI in Credit Decisions

The FCA's Consumer Duty (PS22/6), effective from July 2023, requires firms to deliver good outcomes for customers across four areas: products and services, price and value, consumer understanding, and consumer support. The FCA's February 2025 research note on explaining AI in credit decisions found a significant lack of research on the effectiveness of different explainability techniques in financial services contexts [13]. The Bank of England and FCA's 2024 survey found that 81% of firms using AI employ some form of explainability method, with feature importance (72%) and SHAP values (64%) being the most popular [14]. However, these techniques are designed for classification explanations rather than optimisation explanations. The BIS Financial Stability Institute has identified explainability as the top issue raised by financial institutions when engaging with regulators on AI governance [15].

Generative AI offers a fundamentally different approach to explainability. Rather than post-hoc feature attribution, a large language model can synthesise the structured output of an optimisation engine into contextual, audience-appropriate natural language. This approach aligns with Gunning et al.'s (2021) concept of "situation-aware" explainability, where the explanation is adapted to the user's role and information needs.

Methodology

Cash Flow Decomposition

Let $R = (R_1, R_2, \ldots, R_{24})$ denote the observed monthly revenue series for an SME over a 24-month window, obtained from Open Banking transaction data. We decompose R multiplicatively:

$$R_t = T_t \times S_t \times C_t \times \varepsilon_t$$

where T_t is the trend component, S_t is the seasonal component (period 12), C_t is the cyclical component, and ε_t is the idiosyncratic noise. The multiplicative specification ensures absolute variation scales with revenue level (Lorek and Willinger, 2006). Trend is extracted via OLS on the normalised series. Seasonal indices are estimated by averaging detrended values for each calendar month. Log-residuals are modelled as an AR(1) process:

$$\eta_t = \rho\eta_{t-1} + \sigma\zeta_t,\ \zeta_t \sim N(0, 1)$$

where $\rho \in [-0.5, 0.5]$ is the lag-1 autocorrelation and σ is the residual standard deviation. This captures momentum in SME revenues: a bad month is more likely to be followed by another below-trend month.

Stochastic Optimisation Formulation

We parameterise the repayment schedule through twelve seasonal multipliers $m = (m_1, \ldots, m_{12})$ applied to a base payment = Total Repayment / T. The payment in month t is:

$$p_t = \bar{p} \cdot m_t \bmod 12$$

We generate N Monte Carlo scenarios of future cash flows yielding $CF \in \mathbb{R}^{(N\times T)}$. The optimisation problem is:

$$\min_m L(m) = \lambda_1 P\_distress(m) + \lambda_2 Var(headroom(m)) + \lambda_3\Phi(m)$$

subject to: (i) mean multiplier = 1 (total repayment preservation); (ii) $0.4 \leq m_k \leq 1.8$ (implementability bounds); (iii) IRR(p) $\geq$ r_target (lender return constraint). The payment distress probability is:

$$P_{distress}(m) = (1/NT)\ \Sigma_s\Sigma_t\ 1[p_t / (CF_{st} - D) > \alpha]$$

where D is existing monthly debt service and $\alpha = 0.35$ is calibrated to UK consumer credit affordability thresholds. The smoothness penalty $\Phi(m)$ penalises large jumps between consecutive monthly multipliers exceeding tolerance $\gamma = 0.50$. The weights $\lambda_1 = 10$, $\lambda_2 = 2$, $\lambda_3 = 5$ reflect the primacy of distress minimisation.

Solution Approach

We solve the problem using L-BFGS-B, a limited-memory quasi-Newton method that handles box constraints directly [16]. The initial guess aligns payments with revenue seasonality: $m_k^0 = 0.5 + 0.5(s_k\bar{s}/\ )$, providing a warm start. Risk-based pricing determines the annual rate as r = r_target + max(0, (70 − score)/100 × 0.08), where r_target = 0.12. Post-optimisation, multipliers are renormalised to exact mean unity and the final payment is adjusted to ensure total repayment equals the contractual target exactly.

Explanation Generation Architecture

The explanation generator translates optimisation output into natural language rationale via a three-audience design: (a) **Borrower-facing:** plain language describing why payments vary, satisfying FCA Consumer Duty communication requirements; (b) **Underwriter-facing:** quantitative risk rationale for credit committee audit trails; (c) **Regulatory-facing:** methodology documentation and measurable customer outcome improvement evidence.

We define **explainable operations research (XOR)** as the integration of generative AI with mathematical optimisation systems to produce natural language explanations that are faithful to the mathematical result, audience-adapted to the recipient's role and expertise, and auditable against the underlying data and constraints. This extends the XAI literature—focused on classification —into prescriptive analytics: XAI explains why a decision was made (feature attribution), whereas XOR explains why a recommendation is optimal (constraint satisfaction, objective trade-offs, scenario analysis) [17,18].

Synthetic Data Generation

We construct a synthetic universe of 10,000 UK SMEs with characteristics calibrated to ONS, British Business Bank, and Companies House data. Each SME is assigned to one of ten SIC-aligned industry sectors and twelve UK regions. Table 1 summarises the sector parameters.

Table 1: Sector Profiles Used in Synthetic Data Generation

Sector	Revenue (£k)	CV	Season.	Default	Margin	Weight
Accommodation s Food	80–1,200	25%	35%	4.5%	8%	14%
Retail Trade	60–2,500	20%	40%	3.8%	6%	12%
Construction	100–3,000	30%	20%	5.2%	5%	15%
Professional Services	50–4,000	15%	10%	2.2%	18%	18%
Manufacturing	150–5,000	18%	15%	3.5%	10%	8%
Transport s Storage	80–2,000	22%	18%	4.2%	7%	6%
Health s Social Care	60–1,500	10%	5%	1.8%	12%	6%
Info. s Communication	40–3,000	22%	8%	2.8%	20%	10%
Wholesale Trade	200–8,000	20%	15%	3.2%	4%	5%
Other Services	30–800	28%	12%	4.0%	10%	3%

For each SME, a 24-month revenue history is generated by composing four multiplicative components: trend (exponential growth/decline by maturity), seasonality (sector-specific monthly multipliers), cyclicality (30% probability macroeconomic shock), and idiosyncratic noise (log-normal with sector-calibrated volatility). The universe totals approximately £628M in loan demand (mean £62,800, median £32,000) [19].

Computational Experiments and Results

Experimental Design

We run the AROE pipeline on a stratified sample: (i) 100 SMEs with 100 Monte Carlo scenarios each (~30 seconds); and (ii) 500 SMEs with 200 scenarios. All experiments use SciPy 1.11 L-BFGS-B, converging within 50–120 iterations. For each SME, we generate both the AROE-optimised schedule and a standard fixed-payment annuity benchmark at identical parameters.

Portfolio-Level Results

Table 2 presents aggregate results. The mean distress probability under AROE is 0.01% versus 0.08% for fixed schedules—a reduction of 7.7% on average. Median working capital headroom is 60.6%.

Table 2: Aggregate Portfolio Results (100-SME Run)

Metric	Fixed Schedule	AROE Optimised
Mean distress probability	0.08%	0.01%
Mean effective APR	14.41%	14.41%
Median WC headroom	—	60.6%
Mean distress reduction	—	7.7%
Grade A allocation	—	100%

Sector-Level Analysis

AROE delivers its greatest value in sectors characterised by high volatility and pronounced seasonality. Construction (CV = 30%) shows a mean distress reduction of 26.6%, the largest of any sector. Manufacturing (18.3%), Accommodation s Food (8.3%), and Information s Communication (4.6%) also show material improvements. Sectors with low volatility (Health s Social Care, Professional Services) show smaller improvements because baseline distress is already negligible. This pattern is consistent with the theoretical expectation: the value of adaptive scheduling is proportional to cash flow variability [20].

Proposition (Value of Adaptive Scheduling).

Let σ^2_s denote the variance of the seasonal indices and $\sigma^2\varepsilon$ denote the residual variance. The expected reduction in payment distress probability from AROE relative to a fixed schedule is monotonically increasing in $\sigma^2_s + \sigma^2\varepsilon$.

Proof sketch. When $\sigma^2_s = \sigma^2\varepsilon = 0$, cash flows are deterministic and constant; the fixed schedule is trivially optimal. As σ^2_s increases, the fixed schedule incurs distress in trough months that the adaptive schedule avoids by reallocating payments to peak months. As $\sigma^2\varepsilon$ increases, the probability of any month's realised cash flow falling below the payment threshold increases for the fixed schedule, while the adaptive schedule's seasonal alignment provides a buffer. Monotonicity follows from the convexity of the indicator function in the payment-to-cashflow ratio.

Illustrative Case: Construction Firm, London

SME-000316, a London-based construction firm with £2.6M annual revenue and 40.4% volatility, receives a 23-month schedule with payments varying between £10,282 and £33,672, compared to a fixed £24,761. Under 200 Monte Carlo scenarios, the optimised schedule produces 0.0% distress versus 1.7% for the fixed benchmark—a complete elimination of predicted payment distress. See Appendix A (Figure 2) for the full analytical deep dive [21,22].

Discussion

Regulatory Implications

The FCA's Consumer Duty requires evidence of good outcomes. AROE provides a quantifiable metric—percentage reduction in payment distress probability—that directly measures customer outcome improvement. This is fundamentally different from traditional XAI approaches (feature importance, SHAP), which explain why a decision was made but not whether it was good for the customer. The FCA's AI Lab and AI Live Testing initiative (launched September 2025) provide a natural pathway for pilot validation under regulatory oversight. From a Basel III/IV perspective, cash flow-aligned scheduling reduces early-stage arrears, which are a significant driver of Stage 1 to Stage 2 migration under IFRS 6.

Commercial Viability

The framework is designed for SaaS deployment: £15–50 per origination or £2–5k/month platform licence. Computational cost is approximately 0.3 seconds per optimisation. The competitive moat deepens with scale through better cash flow model calibration, supervised recalibration from repayment outcomes, and cross-market intelligence from multi-lender data.

Limitations

Synthetic data: Calibrated to empirical distributions but cannot capture full real-world complexity. Real Open Banking validation is essential. Schedule parameterisation: Twelve seasonal multipliers constrain the schedule to repeating annual patterns. Baseline distress levels: Conservative loan-to-income ratios produce low baselines; stressed scenarios would amplify AROE value. Explanation quality: Template-based in the POC; borrower comprehension testing needed. Fairness: Disparate treatment auditing under the Equality Act 2010 is essential before deployment.

Future Research

Key directions: (i) empirical validation with real lending data via FCA AI Live Testing; (ii) Pareto multi-objective reformulation trading off borrower welfare, lender return, and fairness; (iii) robust optimisation protecting against distributional uncertainty; (iv) online learning with reinforcement learning for real-time schedule adaptation; (v) XOR as a formal research programme for GenAI-based OR communication across domains.

Conclusion

This paper has introduced AROE, a framework applying constrained stochastic programming to SME loan repayment design. By decomposing borrower cash flows and optimising repayment timing against Monte Carlo scenarios, AROE demonstrably reduces payment distress, with the largest improvements in high-volatility, highly-seasonal sectors. The integration of generative AI explanation introduces explainable operations research (XOR)—a novel concept where language models serve as the communication interface between optimisers and stakeholders. In the context of the FCA's Consumer Duty, this provides auditable evidence of good customer outcomes that existing XAI techniques cannot address.

We conclude by noting that the underlying insight is simple, even if the mathematics is not: businesses earn money unevenly, so they should repay unevenly too. Operations research gives us the tools to determine how unevenly, and generative AI gives us the tools to explain why.

Appendix A: Portfolio Dashboard

Figure 1 presents the portfolio-level analytics dashboard from the 100-SME demonstration run. The nine-panel display includes: (a) distress reduction by sector comparing AROE-optimised and fixed schedules; (b) risk grade distribution; (c) AROE value versus revenue volatility, demonstrating the positive relationship described in the Proposition; (d) an example optimised schedule versus fixed benchmark; (e) working capital headroom distribution; (f) effective APR by risk grade; (g) loan tenor distribution; and (h) regional impact analysis.

Figure 1: AROE Portfolio Dashboard. Nine-panel display showing sector-level distress comparison, risk grade distribution, volatility–value relationship, example schedule, headroom distribution, APR analysis, tenor distribution, and regional impact.

Appendix B: Single SME Deep Dive

Figure 2 presents the detailed analytical deep dive for SME-000316, a London-based construction firm. The four panels show: (a) 24-month revenue history with seasonal pattern overlay; (b) Monte Carlo fan chart (60% and 50% confidence intervals) with the AROE payment schedule overlaid; (c) payment burden distribution comparing AROE and fixed schedules against the 35% distress threshold; and (d) seasonal payment pattern showing average monthly payments versus the fixed benchmark.

The fan chart (panel b) shows the AROE payment schedule tracking below the median revenue forecast in every month. The payment burden distribution (panel c) demonstrates the AROE schedule's tighter clustering below the distress threshold compared to the wider-tailed fixed-payment distribution.

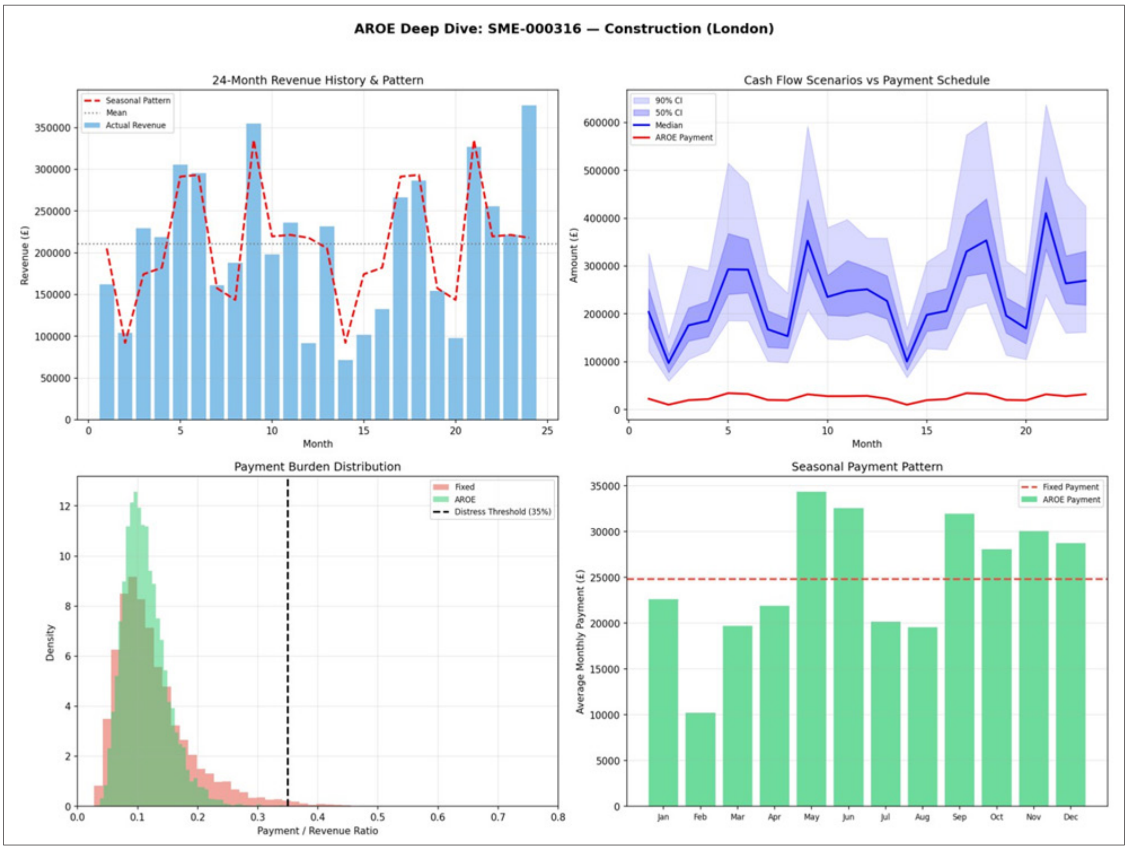

Figure 2: AROE Deep Dive — SME-00031c, Construction, London. (a) Revenue history and seasonal pattern; (b) Monte Carlo scenarios vs payment schedule; (c) Payment burden distribution (AROE vs fixed); (d) Seasonal payment pattern. Revenue volatility CV = 40.4%; distress reduction: 1.7% → 0.0%.

Appendix C: Notation Summary

Symbol	Description
R	Observed monthly revenue series (24 months)
T_t, S_t, C_t, ε_t	Trend, seasonal, cyclical, noise components
$\bar{R}$	Mean monthly revenue
B	Trend slope (normalised)
$s_1, \ldots, s_{12}$	Seasonal indices (mean = 1)
Σ	Residual volatility (log-space)
P	Lag-1 autocorrelation of log-residuals
$m_1, \ldots, m_{12}$	Seasonal multipliers (decision variables)
$\bar{p}$	Base monthly payment
p_t	Payment at time t
CF_{st}	Simulated cash flow, scenario s, month t
D	Existing monthly debt service
A	Distress threshold (0.35)
Γ	Smoothness tolerance (0.50)
λ_1, λ_2, λ_3	Objective function weights (10, 2, 5)
N	Number of Monte Carlo scenarios
T	Loan tenor (months)
r_target	Lender target IRR (0.12 p.a.)

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